Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org

Volume 26, Issues 3, pp. 1057–1070, DOI 10.12694/scpe.v26i3.4225

SMART LAVATORY SOLUTION: INTEGRATING IOT AND DEEP LEARNING MODELS FOR ENHANCED HYGIENE

JIGNA PATEL[*], AESHWI SHAH[†], CHAUDHARI RUSHALI[‡], JITALI PATEL[§], AND VIJAY UKANI[¶]

Abstract. In the current era of smart technology, integrating the Internet of Things (IoT) with Artificial Intelligence has revolutionized several fields, including public health and sanitation. The smart lavatory solution proposed in this paper improves hygiene standards using deep learning models and IoT system. The proposed system collect real-time data from deployed sensors to monitor and assess hygiene conditions regularly. Proposed model consists of four consequent phases as hardware implementation, data preprocessing, application and user interface modules. Rasberry Pi based sensor integration at hardware layer, normalization based techniques at data preprocessing layer, LSTM and GRU based deep learning model at application development layer and mobile notification to the cleaning staff at user interface layer ensure efficiently cleaning and monitoring of lavatory systems. Prior to assessing the proposed model's testing accuracy experiments on the activation functions, optimizer, learning rate, and number of epochs were selected to choose the best to prevent overfitting or underfitting problems. With an accuracy of 98.61%, the proposed system performs better than the conventional approaches.

Key words: Internet of Things, Deep Learning, Long-Short Term Memory, Hygiene, Lavatory

1. Introduction. Traditional lavatory management system is a time consuming process. In order to resolve this issue, an IOT-based approach is introduced which performs real-time monitoring for automated cleaning schedules based on the requirements [22]. Additionally, the earlier system was time-consuming. To resolve these challenges, a smart lavatory is presented as a better solution. IOT-based smart lavatory extends the overall restroom experience in public spaces and proposes real-time monitoring for automated cleaning schedules based on the requirements. It also provides touchless features for improved hygiene, energy-efficient lighting control, occupancy indicators, enhanced user experiences with personalized settings, and integrated air quality sensors [21]. Also, these systems are suitable for high-traffic public areas like malls, airports, and offices since they optimize water and energy use while promoting sustainability. It can monitor washroom occupancy using the Passive Infrared sensor, track soap supplies, clean liquids, and toilet paper, monitor cleanliness levels using different IoT sensors, and send alerts if cleanliness or any other service is required [19, 5]. Moreover, this system enables the management to assign a worker to clean a specific area and remotely operate the cleaning system [18, 20].

The percentage of nations across each continent that have installed smart systems is depicted in Figure 1.1. Asia has the highest rate of acceptance (36.4%), followed by Europe (27.3%). Lower implementation rates are found in North America, Africa, and South America. As many Asian nations appear to be allowing the implementation of smart restroom technology, it indicates their success.

The common perception might be that most restroom germs and bacteria are found on the toilet seat but in reality, bacteria levels are much higher on the floor and high-touch surfaces, including the sink and faucet handles, hand dryers, light switches, doorknobs, as shown in the Figure 1.2. This in turn will spread a variety

[*]Department of Computer Science and Engineering, Institute of Technology, Nirma University, Ahmedabad, Gujarat, India, (jignas.patel@nirmauni.ac.in)
[†]Department of Computer Science and Engineering, Institute of Technology, Nirma University, Ahmedabad, Gujarat, India (21bce012@nirmauni.ac.in)
[‡]Department of Computer Science and Engineering, Institute of Technology, Nirma University, Ahmedabad, Gujarat, India (21bce037@nirmauni.ac.in)
[§]Department of Computer Science and Engineering, Institute of Technology, Nirma University, Ahmedabad, Gujarat, India (jitali.patel@nirmauni.ac.in), Corresponding Author
[¶]Department of Computer Science and Engineering, Institute of Technology, Nirma University, Ahmedabad, Gujarat, India (vijay.ukani@nirmauni.ac.in)

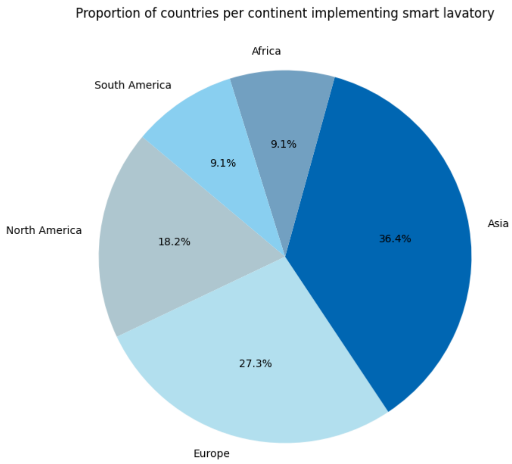

Fig. 1.1: Continents adopting smart lavatory systems [25]

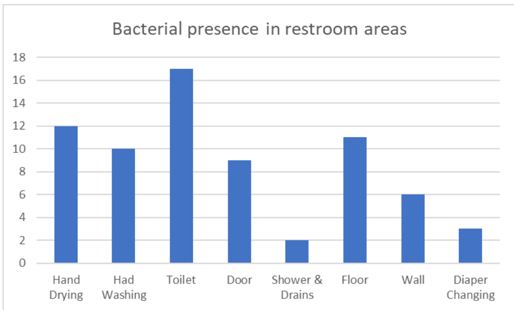

Fig. 1.2: Bacterial presence in restroom areas [27]

of diseases. It has been shown that hand dryers that blow warm air might be absorbing bacteria from the air, and dumping them on the newly washed hands of users. So Paper towels are the most hygienic way to dry hands. Studies have found that frequently touched surfaces such as soap dispensers and toilet handles have bacteria that are both skin-associated and fecal-originated, indicating that surface contact in restrooms is another important mechanism for transmission of illness [27].

Poor hygiene conditions are one of the main issues while using public toilets, as Figure 1.3 shows. The main issue, faced by 55% of users, is unclean restrooms. Other issues can be not having soap or toilet paper, lack of privacy, the toilets being occupied most of the time, etc. These problems show the urgent need to improve the ease of use and hygiene of public restrooms to improve user satisfaction and health [9].

The primary motivation for developing smart lavatory systems is the significant improvement in hygiene standards and user satisfaction [21, 17]. Due to the germs and bacteria found in public restrooms, people are prone to be affected with severe gastrointestinal distress, fever, and fatigue [26]. Table 1.1 shows that diarrheal diseases have a major national and international impact. These diseases appear to be the cause of 1.6 billion deaths worldwide, showing their broad effect on human health.

Users in public areas often face long wait times when using traditional restrooms. This is due to several factors, like inefficient usage, and a lack of real-time information about restroom availability. A key advantage of smart lavatory management is to minimize this queuing frustration by displaying real-time occupancy using the Passive Infrared sensor, and allowing users to report any issues using a real-time feedback system [18]. Additionally, data-driven cleaning schedules maximize the productivity of the cleaning crew by ensuring that

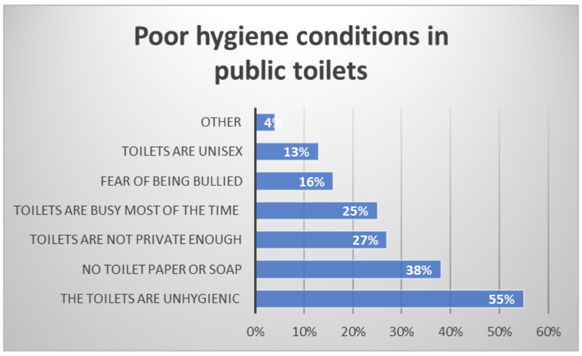

Fig. 1.3: Poor hygiene conditions in public toilets [9]

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Table 1.1: Diseases related to poor hygiene[14]

Diseases	**Deaths(World)**	**Deaths(India)**
E. coli	2.8 million	1.6 million
Salmonella	1.5 million	0.68 million
noroviruses	2.1 million	19
Hepatitis A	3930	424
Diarrhoeal diseases	1.6 billion	2.2 million

bathrooms are cleaned only when necessary [18]. Water-efficient toilets are another crucial component of the system; they are designed with faucets that use less water for hand washing or flushing and reduce water waste by ensuring fixtures are only turned on when necessary [2]. Moreover, when the restroom is unoccupied, the motion sensors can automatically adjust the ventilation and lighting, saving energy [16].

This paper presents the implementation of a deep learning model, namely Long-Short Term Memory (LSTM), in conjunction with the Internet of Things (IoT) to create a smart lavatory management system. The system can alert janitors to clean the restrooms when needed, based on parameters such as gases, temperature, humidity, and occupancy, and detect foul smells. This approach enhances efficiency by optimizing cleaning schedules, saving both time and costs, while also promoting energy efficiency. We implemented this proposed work into practice in the specific washrooms of Nirma University's educational campus. The authors have ensured that notifications are provided correctly when needed and have reduced false alarms by using LSTM and GRU. Our smart restroom system's implementation of LSTM enhances its capacity to provide precise forecasts, guaranteeing better hygiene and upkeep while optimizing resource usage.

2. Related Work. The development of smart toilet technologies has been explored over the past years, as described in Table 2.1, by integrating IoT, machine learning, and deep learning to improve hygiene, user experience and resource efficiency. Lokman et. al. proposed an IoT-based smart toilet system that included genetic algorithms, ARIMA, KNN, and SVM models [11]. This helped to improve reliability and reduce cleaning and energy costs. However, this proposed model had limitations. Similarly, [7] aimed to elevate public health and sanitation by using micro-controllers and PCA for health screening. While this method improved cleanliness in public toilets, it faced issues related to medical test results.

Later Chandra et. al., developed a device auto calibration model using gas sensors and user feedback to create a hygiene monitoring system [4]. However, this system was expensive due to sensor calibration and manual inspection biases. [3] implemented an IoT-based public toilet management system along with occupancy monitoring using Arduino and ultrasonic sensors. Then, [23], also developed an IoT-based system for detecting gas and turbidity levels using Node-MCU micro-controller.

Anto et. al. and Parab et. al., implemented an automated cleaning system to improve public hygiene

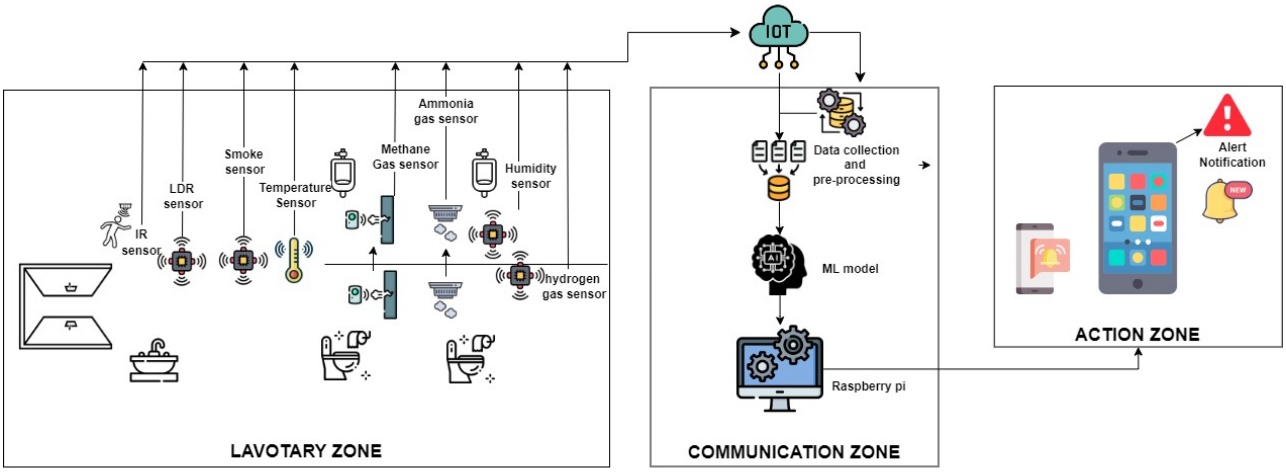

Fig. 3.1: Block Diagram of proposed system

but faced difficulties like resource unavailability, and complex screening mechanisms [1, 24]. Dhamale et. al. developed a system to monitor janitor activities and ensure real-time maintenance of public toilets but the high cost of a fully automated system is a major drawback [6].

Kadam et. al. and Mahalsekar et. al. have focused on providing contactless solutions and centralized monitoring systems to help prevent the spread of diseases caused by public toilets [10, 12]. According to [15], authors have proposed an automated monitoring and alert system for workers to clean the restrooms. Horadi et. al. have emphasized enhancing hygiene in public toilets using MQTT, HTTP, and predictive maintenance models [8].

The integration of IoT, ML, and DL in smart toilet systems has significantly improved public hygiene and resource efficiency. But, there are challenges such as sensor accuracy, costs, etc. For this, we implemented DL based approach(LSTM) for improving efficiency and hygiene. Model detailing is mentioned in a further section of the paper.

After reviewing the above different approaches we found that most of the papers were based on IoT and very few of them included the ML/DL approach. So in this paper, we have implemented the DL(LSTM) approach for improving the accuracy of the given system.

3. Proposed Model. A smart lavatory system is a modern approach to maintaining hygiene by collecting and analyzing sensor data, which is then processed by the DL model (LSTM) to predict whether the lavatory needs cleaning and thus send alerts to staff through the mobile application if required. As shown in Figure 3.1, The first zone is the lavatory zone, where sensors are placed, including a temperature sensor, ammonia gas sensor, VOC (smoke detection) sensor, LDR sensor, methane gas sensor, and IR sensor. Whenever a user enters the lavatory, each sensor provides different readings based on the user's activity. These readings are then combined and transmitted to the second zone, the communication zone, via the IoT device [13]. In the communication zone, data preprocessing is performed before it is fed into the DL model. The LSTM model is selected because the data is collected in real time, and LSTM is more suitable for continuous or sequential data, providing high accuracy. This prediction helps us determine whether cleanliness is required. To facilitate this process, we deployed the Raspberry Pi module. Once the decision is made, the control goes to the action zone where an alert/notification is sent to the staff for cleaning.

For our proposed approach we generate a dataset using various sensors. Figure 3.2 is a sample of the dataset used for the proposed approach. It consists first 10 records taken from sensor readings.

3.1. Real Time Dataset Description. We installed five sensors in each restroom, which contains two washbasins and six toilets. Each sensor was positioned between pairs of washbasins and toilets to monitor various environmental and usage conditions. During the six-month dataset collection period, hourly sensor

Table 2.1: Literature Survey

Ref.	Objective	Methodology	Limitations	IOT	ML	DL
Lokman et. al. 2017	To developing an IoT based smart toilet ensuring user privacy and implementing resource efficient scheduling algorithms	Improved efficiency, reliability and significantly decreased cleaner and energy costs by using genetic algorithms, ARIMA, kNN, and SVM models, as well as schedule optimization for predicting device duration.	• ARIMA model lacks RUL forecasting in specific settings. • Logarithmic transformation reduces time series data variation.	✓	✓	✓
Elavarasi et. al. 2018	Provide clean and hygienic toilet facilities to ensure public health and sanitation standards are met. and also contribute to the Vision of a 'Clean and Disease-Free India' through Innovative Technological Solutions	• Improved efficiency and cleanliness using microcontrollers for environment monitoring and PCA for health screening. • Smart toilets with sensors were implemented to monitor health and save water.	• There might be fault in the results of medical test	✓	✓	
Chandra et. al. 2018	Developing a device model auto-calibration by mapping user ratings to sensor readings and establishing a community benchmark hygiene rating system to enhance the user experience	• The Gas sensor and user ratings were combined to create a hygiene system for hygiene monitoring. • User can give feedback about odor in restroom using sensors installed in the area of restroom through bluetooth.	• Biases in manual inspection. • Sensor calibration for each installation is costly	✓	✓	
Cai et. al. 2019	Developing a system to enhance user experience in public toilets by monitoring toilet condition using IoT for cleanliness and other services like occupancy.	• Implemented Arduino with ultrasonic sensors for toilet monitoring and a Raspberry Pi for sanitation assessment. • IoT improved public toilet cleanliness, user experience and efficiency with a prototype system.	There is no limitations specified in this paper.	✓		
Sujeetha et. al. 2019	Implementing IoT-based sensors for effective toilet management system and spreading awareness about hygiene and maintenance of public toilet	• Sensors detect gas and turbidity levels in toilets for cleanliness. • Data is stored in firebase after processing by NodeMCU microcontroller.	There is no limitations specified in this paper.	✓		
Anto et. al. 2020	Enhancing user experience and janitorial tasks through automated the public hygiene.	• Water level indicator circuit • Automated flushing unit implementation with PIR sensor, servomotor and arduino UNO • Portable external unit for bowel cleaning without human effort.	• Manual cleaning by janitors is not reliable in public toilets. • Existing floor cleaning mechanisms are complex for washroom cubicles.	✓		
Parab et. al. 2020	Continuously monitoring the toilet conditions using sensors and implementing an automated toilet cleaning mechanisms for improving the hygiene.	• Ultrasonic sensor, gas sensor, Arduino controller, Microcontroller, LCD, buzzer, GSM, RFID reader for automatic monitoring system. • Engineering technologies for self-sustained E-toilet, sterilization, water-saving flushing mechanism.	• Unavailability of resources leads to unhygienic toilets. • Inadequate pay and safety equipment for maintenance staff.	✓	✓	
Dhamale et. al. 2020	Implementing a system to track the activities of janitor, thus ensuring real-time monitoring and maintenance of public toilets.	• Detecting unhygienic toilets using gas sensors like MQ-135. • Track worker activities using infrared sensors • Ultrasonic sensor at entrance to count number of toilet users.	• Fully automated systems are costly, and thus not feasible for all public toilets. • Monitoring in developing countries done manually, neglect in some regions.	✓		
Gong et. al. 2020	Research and analyze the development of smart toilets, focusing on their history, stages of development, and market penetration in different countries	• Smart toilet development divided into three stages: birth, growth, maturity. • Domestic smart toilet market growth from 2016 to 2020. • Quality of domestic smart toilet products improved from 2015 to 2019.	• Low penetration rate of domestic smart toilets, especially in lower-tier cities.			
Kadam et. al. 2021	Developing an IoT-based smart toilet and dustbin for hygiene and safety for implementing contactless solutions to prevent the spread of diseases.	Using efficient sensors for building E-toilets and E-dustbins using IoT technologies	• Accuracy of sensors decreases in sunlight, thus affecting their performance	✓		
Mahalsekar et. al. 2022	Developing a system to monitor public toilets for cleanliness and maintenance based on IoT	• Implementing an IoT based approach using five sensors namely RFID, MQ-135, IR, ultrasonic, and infrared for a centralized monitoring	• Lack of an organized approach to check the hygiene of public restrooms. • Insufficient maintenance and overpopulation lead to in insufficient public sanitation.	✓		
Chenchireddy et. al. 2022	Developing a system to monitor air quality by detecting harmful gases like CO2, smoke, and benzene and sound an alarm when they exceed a certain threshold . Also, the air quality will be displayed in PPM on LCD and website.	• IoT-based air pollution monitoring system with alarm for detecting harmful gases using sensors like MQ135, MQ6, and MQ2. • Serial UART, external interrupts, PWM, and SPI for data transmission	There is no limitations specified in this paper.	✓		
Patil et. al. 2023	Implementing an automated system that monitors and alerts janitors whenever the toilet conditions deteriorate past a certain threshold, thus revolutionizing restroom management practices	• IoT sensors will monitor ammonia, water levels, and motion in restrooms. • Data analytics will gove insights on water levels and occupancy. • A feedback monitoring system to enhance the user experience	• Lack of user interest in public sanitation affects cleanliness efforts. • Smart Toilet System focuses on air quality, odor control primarily.	✓	✓	
Horadi et. al. 2024	Enhancing public sanitation by improving cleanliness, hygiene and maintenance of public toilets through IoT-based smart toilet management system.	• System is designed with MQTT and HTTP for data transfer along with hardware implementation using Raspberry Pi and Arduino TTGO. • Implementation water-efficient automatic toilet flushing system using IoT technology by integrating sensors and predictive maintenance models for smart toilets. .	• Limited evaluation of the possibility and efficacy in the real world. • To confirm that the suggested approach is practical and efficient, further research is needed.	✓	✓	
Proposed approach 2024	• Improve Hygiene and resource efficiency. • Improve cleanliness and take care of human health.	• Estimate Clenliness LSTM model is used.	-	✓	✓	✓

Time Stamp	No. of Users(IR)	Gas Sensor(MQ137)-ppm	Gas Sensor(MQ4)-ppm	Gas Sensor(MQ8)-ppm	Luminosity(lux)	VOC	Temperature(DHT22)(in deg. celsius)	Humidity(RH)%
6/1/2024 0:00	9	421.48	5643.2	145.49	5139.34	Yes	46	63
6/1/2024 1:00	11	335.97	4809.5	467.19	2232.15	No	35	27
6/1/2024 2:00	8	94.51	1341.14	536.35	6733.12	Yes	40	32
6/1/2024 3:00	17	413.89	9646.05	462.77	9911.95	Yes	46	51
6/1/2024 4:00	2	465.02	4173.87	947.75	303.5	Yes	2	60
6/1/2024 5:00	19	460.59	4260.73	448.18	7580.68	Yes	48	72
6/1/2024 6:00	9	237	6586.69	929.56	6989.46	Yes	2	10
6/1/2024 7:00	6	189	5131.74	546.97	8217.23	Yes	37	82
6/1/2024 8:00	16	255.05	2235.28	966.4	8305.38	Yes	39	32
6/1/2024 9:00	4	234	658.57	452.71	9139.24	Yes	16	6

Fig. 3.2: Sample of the Dataset

data recordings were used to record important hygiene and usage pattern measurements. This model was implemented on a small scale using the proper sensors and setup equipment. By utilizing more advanced and scalable sensors, this system can be developed to monitor even more areas and cover larger areas. The description of each field and possible dataset values are given below.

1. Time Stamp: The objective of this feature is to track the timing of lavatory usage and environmental conditions, formatted as "MM-DD-YYYY HH". The time is updated on an hourly basis.
2. No. of Users (IR): This feature monitors lavatory occupancy to optimize cleaning schedules and improve overall hygiene management based on user density as detected by an infrared sensor. The values range from 1 to 20, reflecting fluctuations in lavatory usage.
3. Gas Sensor(MQ137)-ppm: The purpose of this feature is to detect ammonia levels helps in assessing air quality and control unpleasant odors, ensuring a healthier environment. The sensor detects values in the range of 5 ppm to 500 ppm.
4. Gas Sensor (MQ4) - ppm: This feature monitoring methane levels is critical for detecting leaks and ensuring safety in enclosed spaces, as well as maintaining proper air ventilation. The sensor detects values within the range of 100 ppm to 10,000 ppm.
5. Gas Sensor (MQ8) - ppm: The objective of this feature is to identify the presence of hydrogen, a potential safety hazard. The detection range spans from 100 ppm to 1,000 ppm.
6. Luminosity (lux): This feature captures the light intensity in the lavatory, measured in lux using an LDR sensor. The recorded values range from 5 lux to 10,000 lux, indicating varying lighting conditions. Maintaining optimal lighting ensures user comfort and energy efficiency, enabling smart lighting adjustments based on current conditions.
7. VOC (Volatile Organic Compounds): The purpose of this feature is to detect VOCs to indicate the presence of various volatile organic compounds, including cigarette smoke. It provides a binary value (yes/no). It helps in improving air quality and alerting users or staff for immediate action.
8. Temperature (DHT22) - °C: This feature records the temperature in the lavatory in degrees Celsius The detected values range from -40°C to 80°C. Monitoring temperature ensures comfort and can be used to regulate heating or cooling systems in the lavatory, contributing to energy efficiency.
9. Humidity (RH): This feature measures the relative humidity which is crucial for maintaining hygiene, preventing mold growth, and ensuring a pleasant user experience in enclosed spaces with values ranging from 0% to 100%.

3.2. Data analytics model. Long Short-Term Memory (LSTM) network is a specialized type of recurrent neural network (RNN), that is used for modeling long-term dependencies within sequential data. Due to its unique architecture, which can successfully capture temporal dynamics over long periods, it forms the basis in the fields of real-time data analysis and sequence prediction. It can update and maintain a memory cell, or internal state, during time steps. The structure of the architecture includes:

- Input Gate: It decides what new information should be added to the cell state. It has two parts: the input activation, for regulating the extent to which new information is stored, and the candidate cell state, for representing potential new information derived from the current input and previous hidden state.

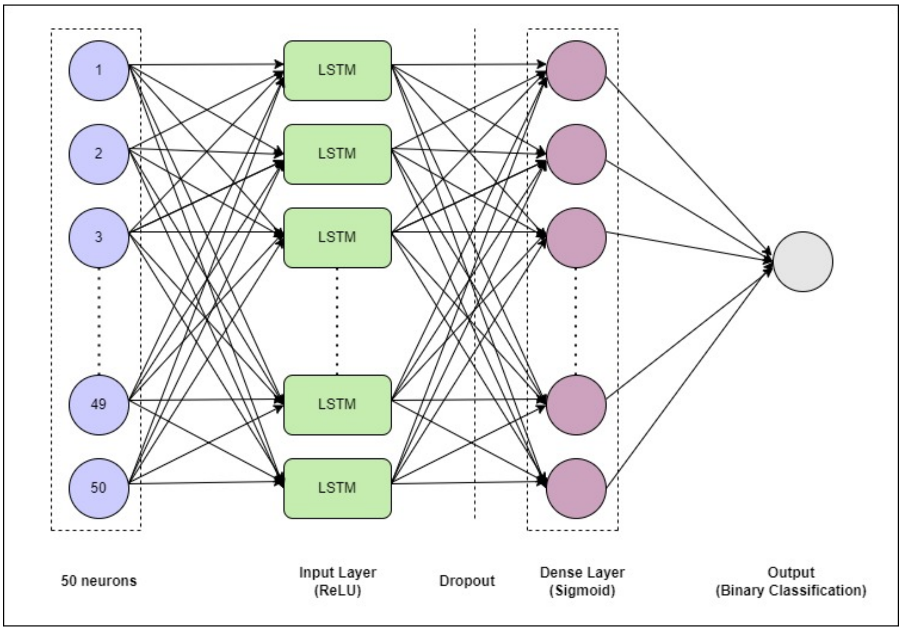

Fig. 3.3: LSTM Architecture

- Output Gate: This gate determines which parts of the cell state should be output as the hidden state for the current time step, contributing to the subsequent time step's computations.

We have implemented LSTM to predict the cleanliness of a lavatory based on data recorded using different sensors. The ability of LSTM to handle sequential dependencies was critical for capturing the dynamic environmental and usage patterns inherent in the data. The architecture included a single LSTM layer with 50 units and a relu activation function, followed by a dropout layer to prevent overfitting and a dense output layer with a sigmoid activation function to produce binary predictions, as shown in Figure 3.3.

3.3. Proposed model workflow. We developed a mobile application based on this proposed approach. In our initial scenario, a dataset is created by collecting readings from various sensors. After preprocessing, we generate the target value for "cleanliness," which determines whether the lavatory needs cleaning. We then apply the LSTM (Long Short-Term Memory) model to predict the target values and assess accuracy. After deploying the model to the cloud, it communicates with the mobile application, allowing workers to receive notifications that indicate when the lavatories need cleaning. This process relies on certain parameters, such as foul smell, temperature, and humidity. Workers are expected to clean the lavatories upon receiving these notifications.

According to this proposed method, a smart lavatory management system may be implemented, improving hygiene. Figure 3.4 illustrates how the model works.

4. Proposed Methodology. This section provides a detailed description of our proposed model in algorithmic form. Subsection 4.1 outlines the step-by-step procedure for generating the dataset using readings from various sensors. The subsequent section explains the data preprocessing process, including normalization and the prediction of the target class based on different recorded parameters. The final algorithm illustrates the training and evaluation process of the LSTM model. Subsection 4.4 details the different parameters such as the number of neurons, train-test split, and hyperparameters including the learning rate and activation functions.

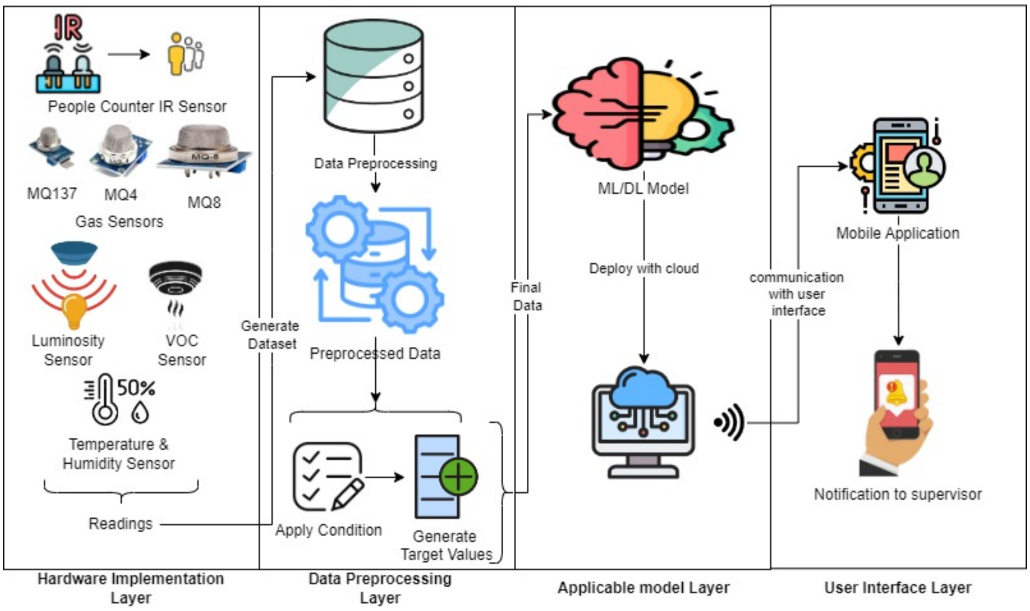

Fig. 3.4: System Architecture of proposed system

4.1. Dataset Generation. In this particular section, Algorithm 1 initializes various sensor readings and records data at regular intervals of one hour. There might be instances where the sensor might fail due to multiple reasons like inaccurate readings, which can result from various factors, including calibration problems, or external interference such as humidity, vibration, or extreme temperature. These issues can be resolved by regularly monitoring sensor behavior and using specialized sensors for extreme environments. The process is performed for a total of six months, appending each sensor reading to the dataset, ensuring an accurate and complete data set for analysis. As the algorithm works over the duration of the six months, it adapts to changes in conditions and sensor performance, which further improves the dataset's quality.

4.2. Preprocessing and Target class Prediction. After dataset preparation, z-score normalization is applied to the model as specified in Algorithm 2. The Z-score normalization process transforms the sensor values to a common scale to confirm that the data is standardized. Also, a new target class called "cleanliness" is initialized, having a value of '0'. Later, this target class changes according to the sensor parameters that were observed. The 'cleanliness' target class is given a value of '1' specifically if any of the criteria exceed their set thresholds. The value '0' remains by the target class if all parameters remain within their threshold.

4.3. ML/DL Model. Algorithm 3 uses a Long-Short Term Memory (LSTM) model in the final step. The LSTM model is trained using the preprocessed sensor data to predict the target class. After training, the model's accuracy in predicting the 'cleanliness' class is assessed, along with its overall accuracy. This evaluation helps identify when sensor data reveals cleanliness problems, enabling accurate and timely predictions.

4.4. Model's Parameters and Hyperparameters. The data is split with 20 percent reserved for testing and the remaining 80 percent for training. Each sample is treated as an individual time step with the number of timesteps set to 1. The sequential class is used to create a linear stack of layers to build the model layer by layer. Each layer contains 50 neurons, allowing it to detect dependencies over time. The activation function applied to the input of each LSTM unit is ReLU (Rectified Linear Unit). The dropout layer is a regularization technique used to prevent overfitting. It randomly sets 20 percent of the input units to 0 during each training update for better generalization. Only one output neuron is required, as it is a binary classification problem (clean or not clean) and using a sigmoid activation function to output a probability value 0 or 1. The Adam optimizer is suitable for large datasets and parameter sets, as it is an adaptive learning rate optimization

Algorithm 1 Generate Dataset

```
Input: All sensors, Time interval //(1 hour)
Output: Dataset with sensor readings
1. Initialize Sensors
  ammonia_value ← (input from MQ137 sensor) // Ammonia (NH3)
  methane_value ← (input from MQ4 sensor) // Methane (CH4) and Natural Gas
  hydrogen_value ← (input from MQ8 sensor) // Hydrogen (H2)
  voc_value ← (input from VOC sensor) // Volatile Organic Compounds
  temp_value ← (input from temperature sensor) // Temperature
  humidity_value ← (input from humidity sensor) // Relative Humidity
2. For Each Time Interval, Collect Data
for t in range(0, total_duration, interval) do
    2.1 Get Current Timestamp
      timestamp ← get_current_time()
    2.2 Read Sensor Values
      occupancy ← read_IR()
      ammonia_value ← read_mq137()
      methane_value ← read_mq4()
      hydrogen_value ← read_mq8()
      light_intensity ← read_luminosity_sensor()
      voc_value ← read_voc_sensor()
      temp_value, humidity_value ← read_temp_humidity_sensor()
    2.3 Append Data to Dataset
      data_entry ← {
        'Timestamp': timestamp,
        'Occupancy': occupancy,
        'NH3 (ppm)': ammonia_value,
        'CH4 (ppm)': methane_value,
        'H2 (ppm)': hydrogen,
        'Light Intensity (lux)': light_intensity,
        'VOC (ppb)': voc_value,
        'Temp (°C)': temp_value,
        'Humidity (%)': humidity_value
      }
end for
```

technique that combines the best features of two existing stochastic gradient descent extensions: AdaGrad and RMSProp. Each time the model weights are updated, the learning rate determines the extent to which the model is adjusted in response to the estimated error. Adam typically employs a learning rate of 0.001 to balance the risk of overshooting the optimal response with the rate of convergence. For binary classification activities, binary Cross-Entropy Loss is used to measure the difference between true labels and expected probabilities.

5. Results and Discusions. This section briefly discusses the performance of the proposed approach using various evaluation measures. Features collected from different sensors were utilized to create the real-time dataset. Although the GRU (Gated Recurrent Unit) model was applied to the dataset, the results did not meet our expectations. The LSTM model performed better than the others on the available dataset. To train this model, we used ReLU and sigmoid activation functions, a learning rate of 0.001, and binary cross-entropy as the loss function (Equation 5.2). These parameters were chosen because our prediction model is designed for binary classification. The model is deployed on the Rasberry Pi module and communicates with a mobile device, sending alerts to the manager.

Different filtering techniques are applied to the model to determine its performance, with accuracy serving as the evaluation metric. In terms of binary classification, if y_i represents the true label for the i-th sample and

Algorithm 2 Predict Target class(Cleanliness)

Input: Dataset with sensor readings
Output: Preprocessed Dataset, Target class value (cleanliness)

1. **Initialize Sensor Values**
   `ammonia_value` ← (input from MQ137 sensor) // Ammonia (NH_3)
   `methane_value` ← (input from MQ4 sensor) // Methane (CH_4) and Natural Gas
   `hydrogen_value` ← (input from MQ8 sensor) // Hydrogen (H_2)
   `voc_value` ← (input from VOC sensor) // Volatile Organic Compounds
   `temp_value` ← (input from temperature sensor) // Temperature
   `humidity_value` ← (input from humidity sensor) // Relative Humidity
2. **Initialize Threshold Values**
   `ammonia_threshold` ← (define threshold for MQ137)
   `methane_threshold` ← (define threshold for MQ4)
   `hydrogen_threshold` ← (define threshold for MQ8)
   `voc_threshold` ← (define threshold for VOC)
   `temp_threshold` ← (define threshold for temperature)
   `humidity_threshold` ← (define threshold for humidity)
3. **Initialize Cleanliness**
   `cleanliness` ← 0
4. **Preprocess Sensor Data**
   4.1 **Convert VOC Sensor Values**
      (a) **for** all i in `range(len(df['VOC']))`: **do**
         i. If `df['VOC'][i]` == 'Yes':
            A. `df['VOC'][i]` ← 1
         ii. Else:
            A. `df['VOC'][i]` ← 0
      (b) **end for**
   4.2 **Standardize Sensor Values**
      (a) `sensor_columns` ← ['NH3 (ppm)', 'CH4 (ppm)', 'H2 (ppm)', 'Light Intensity (lux)', 'Temp (°C)', 'Humidity (%)']
      (b) For all `column` in `sensor_columns`:
         i. $\mu_j \leftarrow \frac{1}{n}\sum_{i=1}^{n} X_{ij}$ // Mean of column j
         ii. $\sigma_j \leftarrow \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_{ij}-\mu_j)^2}$ // Standard deviation of column j
         iii. For all i in `range(len(df[column]))`:
            A. `df[column][i]` ← $\frac{\texttt{df[column][i]} - \mu_j}{\sigma_j}$
5. **Check Thresholds**
   if `ammonia_value` > `ammonia_threshold` **or** `methane_value` > `methane_threshold` **or** `hydrogen_value` > `hydrogen_threshold` **or** `voc_value` > `voc_threshold` **or** `temp_value` > `temp_threshold` **or** `humidity_value` > `humidity_threshold` **then**
      `cleanliness` ← 1
   end if
6. **Output the Result**
   `OUTPUT cleanliness`

$\hat{y}_i$ represents the predicted label, then:

$$\text{Accuracy} = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i) \tag{5.1}$$

where N is the total number of samples.

The loss function typically used in binary classification tasks is binary cross-entropy. The formula for binary cross-entropy is:

Algorithm 3 Model Training

1: **Input Preparation:**
  1.1 Read normalized features
  1.2 Split dataset into train and test set
  1.3 Set hyperparameters (optimizer, learning rate, batch size)
2: **Initialization:**
  2.1 Set the number of epochs sufficiently large
3: **LSTM Function:**
4: **function** LSTM(x_t, e_{t-1})
  4.1 **Local variables:**
    (a) $i_t, o_t \in \mathbb{R}^N$
  4.2 **Model weight matrices:**
    (a) $W_i, W_o \in \mathbb{R}^{N\times M}$
  4.3 **Model bias vector parameters:**
    (a) $b_i, b_o \in \mathbb{R}^N$
  4.4 Compute gates:
    (a) $i_t = \text{relu}(W_i x_t + U_i e_{t-1} + b_i)$
    (b) $o_t = \text{sigmoid}(W_o x_t + U_o e_{t-1} + b_o)$
  4.5 **return** e_t
5: **end function**
6: **Training Procedure:**
  6.1 For each choice of neurons
    (a) For each range of number of replicates
      i. Train the model, monitor training loss
      ii. Repeat
        A. Continue until validation loss at epoch $n \leq$ validation loss at epoch $n+1 <$ validation loss at epoch $n+2$ (where n = Number of epochs)
        B. or maximum epochs reached
      iii. Evaluate model on the test data
      iv. Calculate accuracy
    (b) Until validation loss criteria met
  6.2 End for

$$\text{Binary Cross-Entropy Loss} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right] \tag{5.2}$$

where y_i is the true label for the i-th sample (0 or 1), and $\hat{y}_i$ is the predicted probability for the i-th sample (output of the model's sigmoid function).

As shown in Table 2.1, the Adam optimizer trains the model using various epochs and activation functions. We analyzed the effectiveness of different combinations of activation functions and epoch counts in our experiments, aiming to determine the optimal configuration for enhancing the model's performance. The analysis revealed that training for 300 epochs with ReLU for the input layer and sigmoid for the output layer yielded the best performance compared to other configurations.

The relu activation function is a linear function that helps to avoid the vanishing gradient problem. This allows for faster and more efficient model training. It can also understand complex patterns. The sigmoid activation function works well for binary classification tasks, resulting in either 0 or 1.

The cross-validation technique can be applied to this dataset to assess how well the proposed model generalizes to an independent dataset. Using 20-fold cross-validation, 19 folds are used for training and 1 for testing. After training the model on all folds, we achieved a final avarage accuracy of 98.61%.

The stochastic gradient descent (SGD) optimizer is used to observe the trade-off in model performance (Table 5.2). This robust optimizer is effective in handling large data. However, its simplicity can sometimes be a disadvantage, as it may converge slowly.

Table 5.1: Accuracy with different activation functions and epochs for Adam optimizer

Test No.	Activation Function(i/p)	Activation Function(o/p)	Epochs	Optimizer	Accuracy
Initially	Relu	Sigmoid	100	Adam	-
1	Sigmoid	Relu	100	Adam	Decreased
2	Sigmoid	Sigmoid	100	Adam	Stable
3	Relu	Relu	100	Adam	Increased
Initially	Relu	Sigmoid	200	Adam	-
1	Sigmoid	Relu	200	Adam	Increased
2	Sigmoid	Sigmoid	200	Adam	Decreased
3	Relu	Relu	200	Adam	Increased
Initially	Relu	Sigmoid	300	Adam	-
1	Sigmoid	Relu	300	Adam	Stable
2	Sigmoid	Sigmoid	300	Adam	Stable
3	Relu	Relu	300	Adam	Stable

Table 5.2: Accuracy with different activation functions and epochs for SGD optimizer

Test No.	Activation Function(i/p)	Activation Function(o/p)	Epochs	Optimizer	Accuracy
Initially	Relu	Sigmoid	100	SGD	-
1	Sigmoid	Relu	100	SGD	Stable
2	Sigmoid	Sigmoid	100	SGD	Stable
3	Relu	Relu	100	SGD	Stable
Initially	Relu	Sigmoid	200	SGD	-
1	Sigmoid	Relu	200	SGD	Stable
2	Sigmoid	Sigmoid	200	SGD	Stable
3	Relu	Relu	200	SGD	Stable
Initially	Relu	Sigmoid	300	SGD	-
1	Sigmoid	Relu	300	SGD	Stable
2	Sigmoid	Sigmoid	300	SGD	Stable
3	Relu	Relu	300	SGD	Stable

Adam Optimizer has many advantages over SGD. One of the advantages is that it can maintain a dynamic learning rate. This results in faster convergence and improved performance. While SGD is a reliable optimizer, Adam's adaptive nature allows for better performance in complex models demonstrates that the choice of optimizer and the number of epochs significantly impact model performance. Thus, the optimal configuration for our proposed model is achieved using ReLU as the input layer activation function and combined with sigmoid for the output layer and the Adam optimizer. This setup resulted in a training accuracy of 99.83% and a test accuracy of 98.61%. The Table 5.3 presents a classification report, summarizing the performance metrics for the binary classification model.

The confusion matrix depicted in Figure 5.1 illustrates the performance of our binary classification model. The description of the figure is as follows. The model has correctly classified 6 instances as negative, misclassified 2 negative instances as positive and correctly classified 136 instances as positive and did not misclassify any positive instance as negative. As a result, the model achieved high accuracy by correctly predicting the class for the majority of instances. The precision for the positive class is 0.9855 while for the negative class is 1.0. The recall for the positive class is 1.0 and for the negative class is 0.75.

The matrix highlights the classifier's strength in accurately classifying positive instances, with only a few negative instances misclassified as positive. This type of visualization is crucial for evaluating the model's performance and identifying areas that require improvement.

Table 5.3: Classification Report

Class	Precision	Recall	F1-Score	Support
0	1.00	0.75	0.86	8
1	0.99	1.00	0.99	136
Accuracy	0.99			
Macro Avg	0.99	0.88	0.92	144
Weighted Avg	0.99	0.99	0.99	144

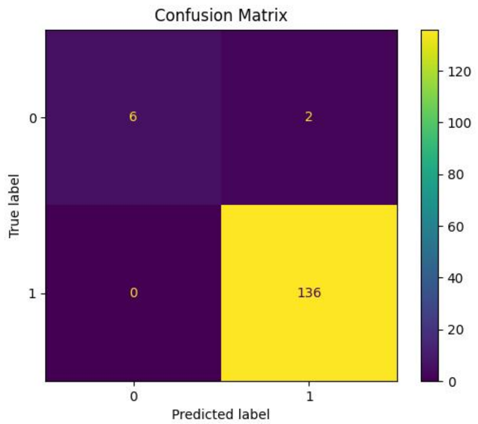

Fig. 5.1: Confusion Matrix of the Binary Classifier Demonstrating Model Performance

6. Conclusion and Future Directions. Smart Lavatory System combines IoT sensors and deep learning models to improve hygiene standards in public restrooms. The system effectively monitors lavatory hygiene conditions by continuously gathering data from environmental sensors. It guarantees timely cleaning and monitoring while offering extra features like occupancy sensors, air quality monitors, and automated dispensers to enhance the overall user experience. Deep Learning Algorithms such as LSTM and GRU, utilize real-time data that enable optimized allocation of cleaning staff and supplies. These automated system also help reduce the wastage of supplies such as hand wash, tissues. Future research will focus on scalability, advancing predictive capabilities, and developing user-friendly interfaces for real-time feedback. The authors aimed to improve the scalability of the existing framework by implementing data partitioning and sharing, distributing the data across multiple nodes and servers while accounting for all the washrooms on the university campus. This approach enhances query performance and simplifies the management of large datasets. The system's scalability is further demonstrated by its integration with a cloud infrastructure, offering elastic stability for handling high volumes of data. Additionally, the use of Deep Learning models such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) further enhances its capability to handle extensive data processing efficiently.Data compression techniques can also be used to save storage costs and increase data transfer rates. Further, these datasets can additionally be processed effectively by implementing a scalable data processing framework like Apache Spark or MapReduce programming. Given that our current model has been designed for a limited workspace, we did not address data security or breach detection. In upcoming larger-scale implementations, we aim to implement RSA encryption to improve data security and defend against potential breaches. The Smart Lavatory Solution has the potential to keep evolving, delivering substantial advantages in public health, sanitation, and resource management, thereby raising hygiene standards.

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Edited by: Jingsha He
Special issue on: Efficient Scalable Computing based on IoT and Cloud Computing
Received: Jun 30, 2024
Accepted: Jan 7, 2025